# Subsurface Visual Transformer Networks for Coral Biodiversity Mapping

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## ABSTRACT

Coral reefs are among the most diverse ecosystems on Earth, supporting nearly 25% of all marine life despite covering only about 1% of the ocean floor. In addition to their ecological importance, they play a vital role in human livelihoods, with nearly 500 million people depending on them for food, income, and coastal protection. However, coral reefs are increasingly threatened by pollution, climate change, overfishing, and other human activities, leading to significant degradation worldwide. Monitoring and identifying coral species is therefore essential for assessing reef health and implementing effective conservation strategies. Traditional coral identification methods rely heavily on manual observation by experts, which is time-consuming, labor-intensive, and often prone to errors. Moreover, underwater imaging presents additional challenges such as poor visibility, low contrast, varying lighting conditions, and the high visual similarity between different coral species. These factors make accurate and efficient classification a difficult task. To address these challenges, this project proposes an automated image-based coral classification system using advanced deep learning techniques. Specifically, Vision Transformers (ViT) are employed to extract rich and contextual features from underwater images. Unlike conventional convolutional neural networks, ViT leverages attention mechanisms to capture global relationships within images, improving classification performance. The extracted features are then integrated with powerful machine learning classifiers, including Natural Gradient Boosting (NGBoost), Histogram Gradient Boosting (HGB), Extreme Gradient Boosting (XGBoost), and Skope Rules Classification (SRC). Among these approaches, the ViT combined with Skope Rules Classification (ViT + SRC) demonstrates superior performance, achieving higher accuracy and effectively handling imbalanced datasets. The proposed system provides a reliable and efficient solution for large-scale coral species classification, supporting marine research and conservation efforts.

## 1.1 INTRODUCTION

India is surrounded by major sea bodies that strongly influence its climate, economy, and coastal life. These sea surfaces play a vital role in monsoons, marine biodiversity, trade, and fishing. The sea surfaces are Arabian Sea, Bay of Bengal, Indian Ocean. Overall, these sea surfaces are crucial to India's weather, economy, environment, and coastal communities. Andhra Pradesh has one of the longest coastlines in India, stretching about 974 km along the Bay of Bengal. The coastal region is very important for fishing, agriculture, ports, trade, and climate. The coastal areas are Srikakulam (Uttarandhra coast), Vizianagaram, Visakhapatnam, Anakapalli (coastal mandals), Kakinada (East Godavari region), Guntur (coastal mandals – Bapatla region), Nellore (Sri Potti Sriramulu Nellore). The coastal regions of Andhra Pradesh support fishing, ports, agriculture, aquaculture, tourism, and industry. They also influence weather patterns and are prone to cyclones, so coastal management and protection are very important.

Figure 1 shows, Coral reefs are one of the most valuable marine ecosystems. They provide a natural habitat for a wide variety of fish, crabs, mollusks, and other marine organisms. Many coastal communities depend on coral reefs for fishing, as reefs support breeding and nursery grounds for commercially important fish species. Coral reefs are widely used for tourism and recreation. Activities such as snorkeling, scuba diving, and reef-based tourism generate income and employment for coastal populations.

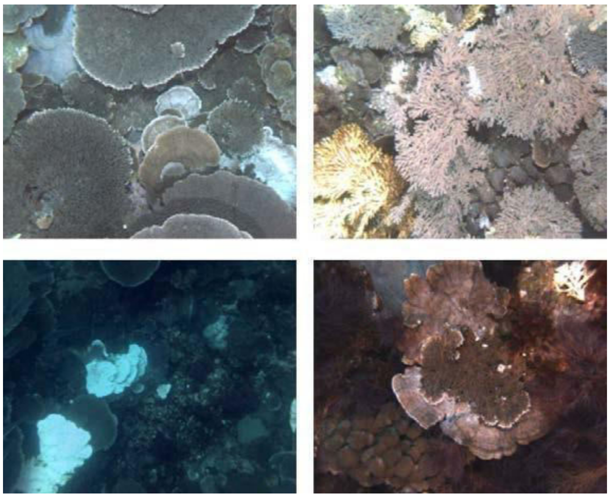

Figure 1: Coral reefs

Marine biology scientists' study coral reefs because they are some of the most important yet fragile ecosystems on Earth. By spending time underwater, collecting samples, and using modern tools like satellite images and underwater cameras, scientists try to understand how corals grow, how different species live together, and how reefs react to changes in the environment. Coral reefs provide many ecological and economic benefits. They support nearly 25% of all marine species, even though they cover a very small portion of the ocean floor. Coral reefs cover less than 1% of the ocean floor but support about 25% of marine life. Coral reefs include Bleached corals, Boulder corals, soft corals, Plate corals, Healthy corals, Branched corals Marine biology research clearly shows that coral reefs are not just underwater structures but living ecosystems that support marine life, protect coastlines, and sustain human communities. Scientific studies help us understand their value and highlight the urgent need to protect and restore coral reefs so that future generations can continue to benefit from them.

## 2. LITERATURE SURVEY

Shao, et al. [1] proposed a new multilabel method for automatically detecting coral reef conditions and extracting ecological information. A dataset containing over 20,000 high-resolution coral images of different health conditions and stressors was constructed based on the field survey. Seven representative deep learning architectures were tested on this dataset, and their performance was quantitatively evaluated using the F1 metric and the match ratio. Based on this evaluation, a new method utilizing the ensemble learning approach was proposed. Han, et al. [2] developed a large vision-language models like CLIP have greatly enhanced zero-shot and low-shot classification capabilities for various visual tasks. However, these models struggle with fine-grained coral-related tasks due to a lack of specific knowledge. To bridge this gap, we compile a fine-grained coral image dataset consisting of 16,659 images with taxonomy labels accompanied by morphology-specific text descriptions for each species. Based on the dataset, they propose CORALAdapter, integrating two complementary kinds of coral-specific knowledge with general knowledge learned by CLIP. Dou, et al. [3] proposed UKANFormer, a novel se-mantic segmentation model designed to achieve high-precision mapping under noisy supervision derived from Allen Coral Atlas. Building upon the UKAN architecture, UKANFormer incorporates a Global-Local Transformer (GL-Trans) block in the decoder, enabling the extraction of both global semantic structures and local boundary details. In experiments, UKANFormer achieved a coral-class IoU of 67.00% and pixel accuracy of 83.98%, outperforming conventional baselines under the same noisy labels setting. Li, et al. [4] presented a literature review on underwater coral image segmentation, focusing on the deep learning implementation pipeline. Furthermore, they introduce a new densely annotated dataset specifically designed for the semantic segmentation of underwater coral images. They systematically evaluate State-of-the-Art (SOTA) methodologies and novel techniques not previously applied to coral image semantic segmentation using the proposed dataset. Then discussed their feasibility in this context. Lawson, et al. [5] developed deep learning and citizen scientist analysis methods that had different but complementary strengths depending on coral category. When the best performing analysis method was used for each category in all images, mean estimates from 8086 images of percent benthic cover of branching *Acropora*, plating *Acropora*, and massive-form coral were ~ 99% accurate compared to expert assessment, and > 95% accurate at all coral cover ranges tested. Site-level accuracy of 95% was attainable with 18–80 images. Nawaz, et al. [6] This study reviews the current deep-learning techniques used for monitoring and classification of the seagrass. It discusses the key methodologies, datasets, and progress in this area. This study not only examines the well-known challenges such as limited availability of data but provides a novel, structured taxonomy of deep learning techniques tailored for the monitoring of seagrass, highlighting their unique advantages and limitations within diverse marine environments. McCammon, et al. [7] addressed the problem by training a YOLOv5 convolutional neural network (CNN) to automate the detection of tonal and pulsed fish calls in spectrogram data from five tropical coral reefs in the U.S. Virgin Islands, building from over 22 h of annotated data with 55 015 fish calls. The network identified fish calls with a mean average precision of up to 0.633, while processing data over 25× faster than it is recorded. Coelho, et al. [8] proposed the accelerated neutron beam experiments, they study the reliability of six ViTs on the Coral TPU and four microbenchmarks. According to our data, the internal size of attention heads has negligible impact on the failure-in-time (FIT) rate of the model compared to increasing the number of heads in the model; furthermore, our results show that employing convolutions in the patch embedding reduces the FIT rate of the model. Manikandan, et al. [9] proposed an integrated model that combines the strengths of a Vision Transformer (ViT) and Transfer Learning (TL). The paper introduces a novel methodology for the classification of marine species images by integrating the capabilities of a Amended Dual Attention oN Self-locale and External (ADANSE) Vision Transformer and a DenseNet-169 Transfer Learning model. The ADANSE-ViT, serving as the foundational architecture, excels in capturing long-range dependencies and intricate patterns in large-scale images, forming a robust basis for subsequent classification tasks.

Rubbens, et al. [10] provided a quick primer on machine learning techniques and vocabulary. They built a database of ~1000 publications that implement such techniques to analyse marine ecology data. For various data types (images, optical spectra, acoustics, omics, geolocations, biogeochemical profiles, and satellite imagery), they presented a historical perspective on applications that proved influential, can serve as templates for new work, or represent the diversity of approaches. Reshma, et al. [11] analyzed the performance of Convolutional Neural Networks (CNN) through different taxonomic ranks to classify the underwater images. They have used 1,15,296 images from the CoralNet database comprising 104 species. A classifier was developed by fine-tuning the pretrained ResNet34. The developed CNN classified 87.5% of 34,543 test images correctly to species level and 91.78% to genus level. The average classification recall on species level was 83.99%. Dung, et al. [12] evaluated the mapping accuracy of coral covers using PlanetScope satellite pictures with the Artificial Neural Network (ANN) method surrounding Cu Lao Xanh Island in Binh Dinh province. To adjust for the sun glint effect, the bands were corrected using the Hedley technique. After that, the Depth-Invariant Index technique was utilized to reduce the influence of the water column, and the ANN algorithm was employed for mapping. Hard coral, soft coral, seagrass, deep water, and bare bottom were identified as the five kinds of benthic habitat. Mahmood, et al. [13] introduced Automated technology to monitor the health of the oceans would allow for transformational ecological outcomes by standardizing methods to detect and identify species. This paper aims to automate the analysis of large available AUV imagery by developing advanced deep learning tools for rapid and large-scale automatic annotation of marine coral species. Such an automated technology would greatly benefit marine ecological studies in terms of cost, speed, and accuracy. aphael, et al. [14] introduced the methods used in each of the advances in the application of deep learning (DL) to coral research that took place between the years: 2016–2018. DL has unique capability of streamlining the description, analysis, and monitoring of coral reefs, saving time, and obtaining higher reliability and accuracy compared with error-prone human performance. Coral reefs are the most diverse and complex of marine ecosystems, undergoing a severe decline worldwide resulting from the adverse synergistic influences of global climate change, ocean acidification, and seawater warming, exacerbated by anthropogenic eutrophication and pollution. Edinger, et al. [15] classified using triangular diagrams based on coral morphology; these taxonomy independent classes predict several aspects of conservation value for coral reefs. Conservation classes (CC's) of 1, 2, 3 or 4 were assigned to reef sites dominated by massive and sub-massive corals (CC 1), foliose or branching non-Acropora corals (CC 2), Acropora corals (CC 3), or approximately equal mixes of these three end-members (CC 4). When applied to 15 Indonesian coral reefs, aggregate conservation class, the average of the conservation class of all sites on that reef, was a reliable predictor of coral species richness, habitat complexity, and rare coral species occurrence.

## 3. PROPOSED SYSTEM

The proposed system as shown in Figure 2 focuses on accurate coral species classification using a combination of deep learning–based feature extraction and advanced machine learning classifiers. The process begins with a well-structured coral reef image dataset and applies image preprocessing to enhance underwater image quality. Vision Transformer (ViT) is used to extract high-level and meaningful visual features from coral images. These features are then classified using existing models such as NGBoost, XGBoost, and Histogram-based Gradient Boosting (HGB), and further improved using the proposed SRC. A detailed performance comparison is carried out to evaluate all models, followed by coral species prediction on unseen data.

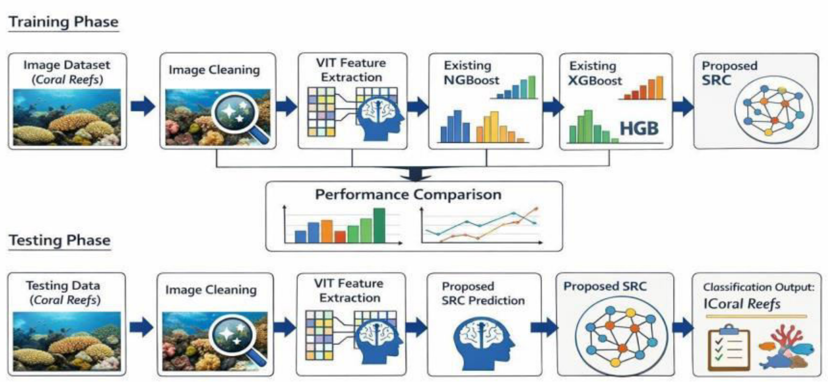


Figure 2: System Architecture

**Step 1 : Coral Dataset:** The methodology starts with collecting a coral reef image dataset that contains different coral species captured in underwater conditions. The dataset includes variations in lighting, depth, background noise, and coral shapes, which helps the model learn real-world reef diversity. Each image is labeled with its corresponding coral species to support supervised learning.

**Step 2 : Image Preprocessing:** In this step, raw coral images are preprocessed to improve visual clarity and consistency. Noise reduction, resizing, normalization, and color correction are applied to handle underwater distortions such as low contrast and color loss. This step ensures that all images have a uniform format and quality before being passed to the feature extraction stage.

**Step 3 : ViT Feature Extraction:** Vision Transformer (ViT) is used to extract deep features from the preprocessed coral images. The images are divided into fixed-size patches, which are converted into embeddings and processed using self-attention mechanisms. ViT captures both local coral textures and global reef patterns, producing rich feature representations that are suitable for accurate coral species classification.

**Step 4 : Existing NGBoost Classifier:** The extracted ViT features are first passed to the existing NGBoost classifier. NGBoost focuses on probabilistic classification by predicting the uncertainty along with coral species labels. This helps in understanding how confident the model is when classifying similar-looking coral species in complex reef environments.

**Step 5 : Existing XGBoost Classifier:** Next, the same feature set is evaluated using the existing XGBoost classifier. XGBoost builds an ensemble of decision trees sequentially to minimize classification errors. It efficiently handles nonlinear relationships between coral features and species classes, making it a strong baseline model for coral classification.

**Step 6 : Existing HGB Classifier:** The Histogram-based Gradient Boosting (HGB) classifier is then applied to the ViT features. HGB improves training speed by grouping continuous feature values into bins. This makes it suitable for large coral datasets while maintaining good classification accuracy.

**Step 7 : Proposed SRC:** The proposed SRC model is introduced to enhance coral species classification performance. SRC combines rule-based learning with refinement, allowing it to capture both stable coral patterns and subtle variations across species. By iteratively refining decision rules, SRC improves discrimination between visually similar coral species commonly found in reef ecosystems.

**Step 8 : Performance Comparison:** In this step, all classifiers are evaluated and compared using standard performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix. The comparison highlights the strengths and weaknesses of each model and demonstrates the effectiveness of the proposed SRC model over existing classifiers.

**Step 9 : Prediction from Dataset:** After selecting the best-performing model, coral species predictions are generated for unseen test images. The model assigns a coral species label based on learned features, helping in automated reef monitoring and coral biodiversity assessment.

**Step 10 : Integration with Tkinter:** Finally, the complete coral species classification system is integrated with a Tkinter-based graphical user interface. This interface allows users to upload coral images, view predictions, and analyze classification results easily. The integration makes the system practical, interactive, and suitable for real-time coral reef monitoring applications.

### 3.1 ViT Feature Extraction

Vision Transformer (ViT) shown in Figure 3 is used to extract meaningful features from preprocessed underwater coral reef images for the application of coral species classification. The input to the method is preprocessed coral image data where noise, color distortion, and size variations caused by underwater conditions have already been corrected. These images are then transformed into a set of discriminative ViT features as the output, which capture both fine coral textures and broader reef patterns needed for accurate species identification.

**Step 1 : Input Coral Image Representation:** The operation begins by taking preprocessed coral images as input, where each image represents a specific coral species from the reef ecosystem. These images are resized to a fixed resolution required by the ViT model, ensuring consistency across all coral samples. This uniform representation allows the model to focus on learning coral-specific visual characteristics rather than size or scale differences.

**Step 2 : Patch Formation from Coral Images:** Each coral image is divided into small, non-overlapping patches that act as visual tokens. Every patch contains localized coral information such as surface texture, polyp structure, or branching patterns. By converting the coral image into a sequence of patches, the model treats the image similarly to a sequence of words in a sentence, making it suitable for transformer-based processing.

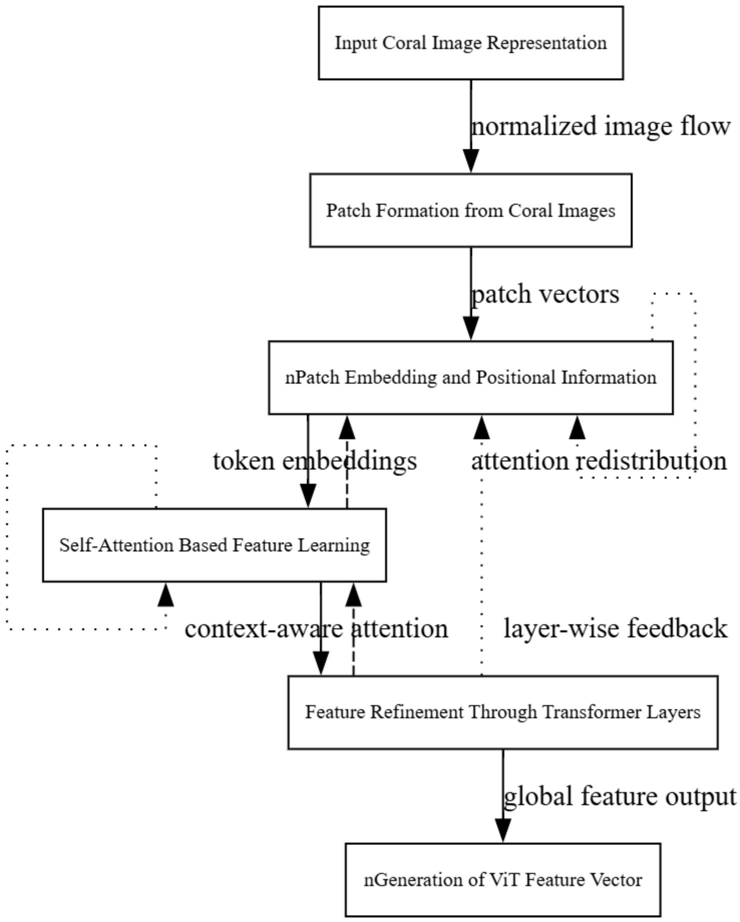


Figure 3: ViT Feature Extraction

**Step 3 : Patch Embedding and Positional Information:** The coral image patches are flattened and mapped into numerical vectors called patch embeddings. Positional information is added to each embedding to retain the spatial arrangement of coral structures within the reef image. This step is important because the relative location of coral features, such as growth patterns or colony shapes, plays a key role in species classification.

**Step 4 : Self-Attention Based Feature Learning:** The embedded coral patches are passed through multiple transformer layers that use self-attention mechanisms. During this process, the model learns how different coral patches relate to each other across the entire image. For example, it can associate coral edges with internal textures or identify repeating patterns within a coral colony. This global understanding helps the model distinguish between visually similar coral species.

**Step 5 : Feature Refinement Through Transformer Layers:** As the coral patch representations move through successive transformer layers, the features become more refined and abstract. Early layers focus on simple coral patterns, while deeper layers capture complex structures such as branching style, surface roughness, and overall coral morphology. This hierarchical refinement enhances the discriminative power of the extracted features.

**Step 6 : Generation of ViT Feature Vector:** In the final step, the transformer output is aggregated into a single feature vector that represents the entire coral image. This ViT feature vector summarizes the most important visual information related to coral species characteristics. These extracted features are then used as input for classifiers such as NGBoost, XGBoost, HGB, or the proposed SRC model to perform accurate coral species classification.

## 4. Results Analysis

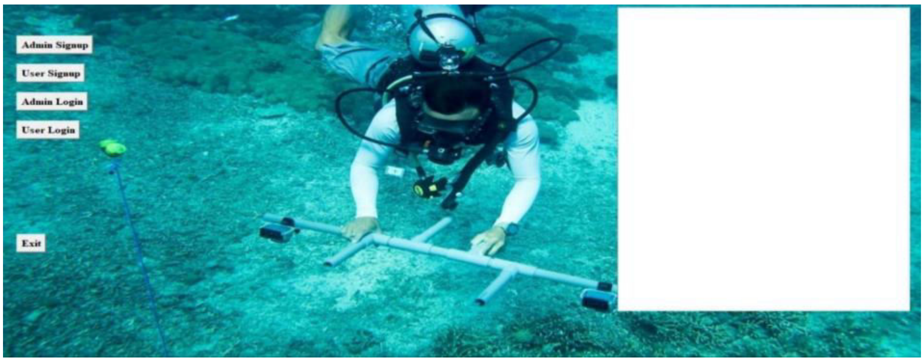


Figure 4 GUI of Research work

Figure 4 shows the graphical user interface (GUI) developed for the research work on Transformers Driven Multi-Class Coral Reef Classification. The interface presents a visually intuitive underwater background representing the real-world coral reef environment, reinforcing the application context of marine ecosystem analysis. On the left side of Figure 4, dedicated control buttons such as Admin Signup, User Signup, Admin Login, User Login, and Exit are provided, enabling role-based access and secure interaction with the system. This design supports both administrative users, who manage datasets and models, and end users, who perform coral reef classification tasks. The large display panel on the right side of Figure 4 is intended for loading underwater coral images and visualizing classification outputs generated by the transformer-based model. Overall, Figure 4 highlights a user-friendly and application-oriented GUI that facilitates seamless interaction with the proposed system, ensuring efficient image input, controlled access, and clear visualization of multi-class coral reef classification results.

Figure 5 illustrates the performance of the proposed SRC model in classifying coral species. Most samples are correctly classified along the diagonal, indicating high accuracy across classes. Bleached, Boulder, Branched, Plate, and Soft Coral show nearly perfect predictions, while Healthy Coral has a few misclassifications. Overall, the matrix demonstrates that the SRC model performs effectively with minimal classification errors across all coral categories.

Figure 6 illustrates the ROC curves of the proposed SRC model using a one-vs-rest approach for multi-class coral reef classification. All six coral classes—Bleached, Boulder, Branched, Healthy, Plate, and Soft Coral—achieve an AUC of 1.00, indicating perfect class discrimination. The microaverage ROC curve also records an AUC of 1.00, confirming the outstanding overall performance of the SRC model.

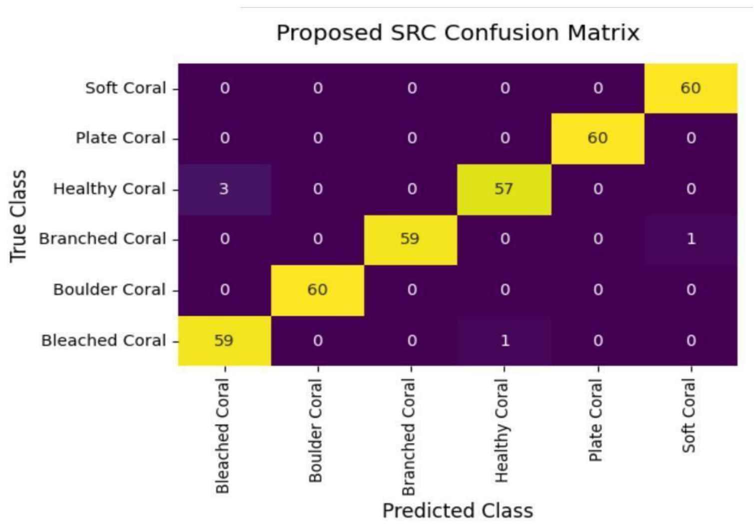


Figure 5: Confusion Matrix of SRC

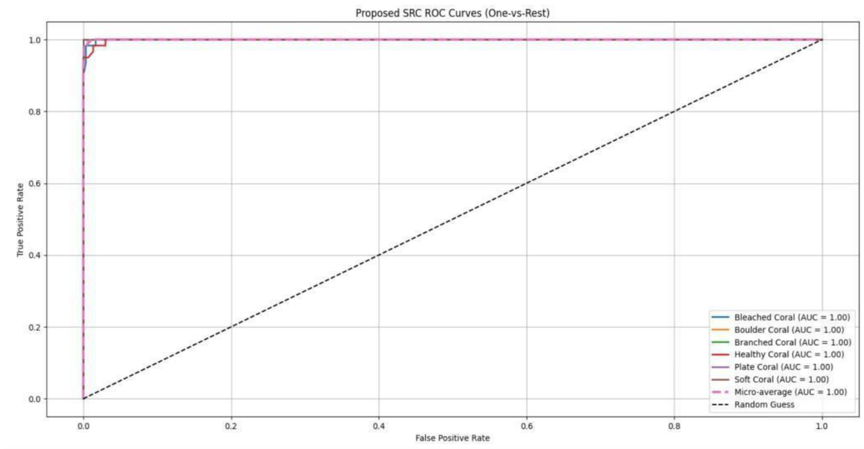


Figure 6: ROC Curve of SRC

Figure 7 shows the prediction and interpretability results of the proposed coral reef classification system for a sample underwater image. As illustrated in Figure 6, the left panel displays the original coral reef image captured in a natural underwater environment, which is provided as input to the model. The middle panel presents the Explainable Artificial Intelligence (XAI)–based coral reef analysis results, indicating that the input image is correctly identified as a coral reef, with coral presence confirmed as true, coral type recognized as massive, health status classified as healthy, visibility assessed as high, and the dominant color detected as green. The right panel in Figure 6 shows the final classification output generated by the model, where the coral is accurately labeled as Boulder Coral. This figure demonstrates the effectiveness of the proposed approach in not only producing accurate coral reef classification results but also providing meaningful interpretability features that enhance transparency and user understanding of the model's decision-making process.

Figure 8 illustrates the prediction results of the proposed coral reef classification system for a branched coral sample. As shown in Figure 8, the left panel presents the original underwater image containing a clearly visible branched coral structure captured in a natural marine environment. The middle panel displays the XAI-based coral reef analysis, confirming that the image is a coral reef with coral presence marked as true, the coral type identified as branched, the health status classified as healthy, underwater visibility assessed as high, and the dominant color detected as blue. The right panel in Figure 8 shows the final model output, where the coral is accurately classified as Branched Coral. This figure demonstrates the capability of the proposed system to correctly identify branched coral formations while simultaneously providing interpretable insights that support transparency.


Figure 7: Prediction Results of Boulder Coral


Figure 8: Prediction Results of Branched Coral

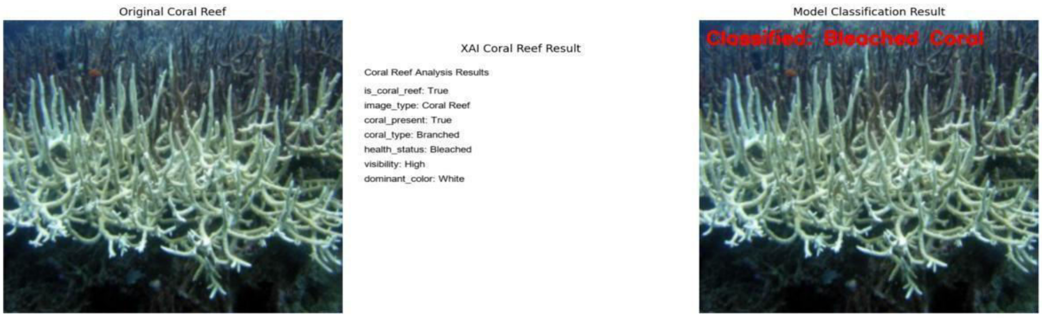


Figure 9: Prediction Results of Bleached Coral

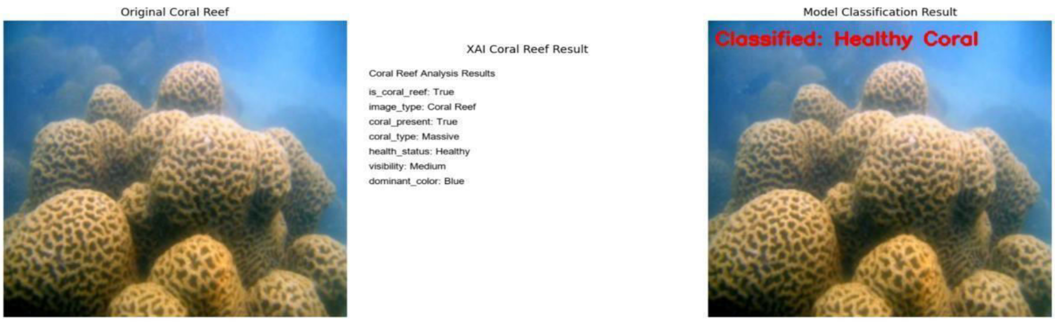


Figure 10: Prediction Results of Healthy Coral

Figure 9 illustrates the prediction results of the proposed coral reef classification system for a bleached coral sample. As shown in Figure 9, the left panel displays the original underwater image containing coral structures with visibly pale and whitened appearance, characteristic of coral bleaching. The middle panel presents the XAI-based coral reef analysis results, confirming that the input image is a coral reef with coral presence marked as true, the coral type identified as branched, the health status correctly detected as bleached, underwater visibility assessed as high, and the dominant color recognized as white. The right panel in Figure 9 shows the final classification output generated by the model, where the coral is accurately labeled as Bleached Coral.

Figure 10 shows the prediction results of the proposed coral reef classification model for a healthy coral sample. The original underwater image demonstrates a well-structured massive coral formation with natural coloration and no visible signs of bleaching or damage. The explainable AI (XAI) analysis confirms the presence of coral and identifies it as a massive coral type with healthy status, medium visibility, and blue as the dominant underwater color. The final classification output, displayed on the image as “Classified: Healthy Coral,” verifies that the model accurately detects and classifies healthy coral reefs, highlighting the effectiveness and reliability of the proposed approach for automated coral reef monitoring and conservation applications.

Figure 11 illustrates the prediction results of the proposed coral reef classification model for a plate coral sample. The original image depicts a distinct flat, disc-shaped coral structure typical of plate corals, captured under clear underwater conditions. The explainable AI (XAI) analysis confirms the presence of coral and identifies it as a plate coral type with a healthy condition, high visibility, and brown as the dominant color. The final model output, shown as “Classified: Plate Coral,” validates the accuracy of the classification, demonstrating the model’s capability to correctly recognize coral morphology and health status, thereby supporting its effectiveness for automated coral reef assessment and monitoring.

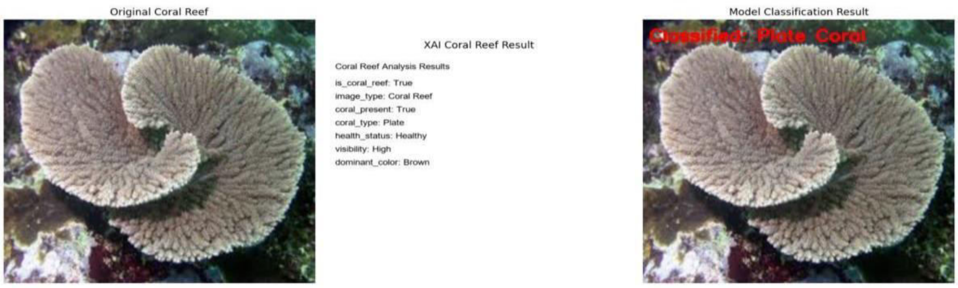


Figure 11: Prediction Results of Plate Coral

Figure 12 presents the prediction results of the proposed coral reef classification model for a soft coral sample. The original image shows flexible, branch-like coral structures with vibrant coloration, which are characteristic features of soft corals, captured under high underwater visibility conditions. The explainable AI (XAI) analysis confirms the presence of coral and identifies it as a soft coral type with a healthy status and blue as the dominant background color. The final classification output, displayed as “Classified: Soft Coral,” demonstrates that the model accurately recognizes soft coral morphology and health, highlighting the robustness and reliability of the proposed approach for automated coral reef monitoring and conservation applications.


Figure 12: Prediction Results of Soft Coral

Table 1 summarizes the performance of different classification methods for multi-class coral reef classification using accuracy, precision, recall, and F1-score. The proposed SRC method achieves the best results, with an accuracy, precision, recall, and F1-score of around 98.6%, demonstrating its superior and consistent classification performance. NGBoost also performs well, achieving approximately 93.6% across all metrics, indicating reliable predictions. XGBoost shows moderate performance with values around 78%, while Histogram Gradient Boosting (HGB) records the lowest results, with performance close to 52%, indicating limited effectiveness for this task. Overall, the results clearly show that the proposed SRC model outperforms the existing methods in accurately classifying multiple coral reef categories.

Table 1: Overall Performance Comparison

| Method | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| **NGBoost** | 93.61 | 93.60 | 93.61 | 93.60 |
| **Histogram Gradient Boosting (HGB)** | 52.50 | 55.03 | 52.50 | 52.66 |
| **XGBoost** | 78.06 | 78.35 | 78.06 | 77.97 |
| **Proposed SRC** | 98.61 | 98.63 | 98.61 | 98.61 |

## 5. CONCLUSION

The experimental evaluation of the proposed Transformers Driven Multi-Class Coral Reef Classification system demonstrates a significant improvement over existing machine learning approach. Quantitative results show that the proposed SRC model achieves an overall accuracy of 98.61%, precision of 98.63%, recall of 98.61%, and F1-score of 98.61%, outperforming NGBoost (93.61% accuracy), XGBoost (78.06% accuracy), and Histogram Gradient Boosting (52.50% accuracy). Class-wise analysis further confirms the robustness of the SRC model, with recall and precision values reaching 100% for Boulder Coral and Plate Coral, and F1-scores of 99–100% across most coral categories. The ROC analysis strengthens these findings, where the proposed SRC model attains a perfect AUC of 1.00 for all six coral classes and a micro-average AUC of 0.9998, indicating near-ideal class separability and minimal false-positive rates. In addition to high numerical performance, the integration of Explainable Artificial Intelligence (XAI) enhances the transparency and interpretability of the classification process. The visual prediction results demonstrate accurate identification of coral types such as Boulder Coral, Branched Coral, and Bleached Coral, along with meaningful contextual attributes including coral presence, health status, dominant color, and underwater visibility. This interpretability aspect makes the system highly suitable for real-world marine monitoring applications, where trust and explainability are essential. Overall, the proposed SRC framework provides a reliable, accurate, and interpretable solution for automated coral reef classification, supporting large-scale ecological assessment and conservation efforts.

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